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An Evaluation of Hourly Average Wind-Speed Estimation Techniques

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ABSTRACT

Wind-speed time series are often used in computer models to estimate the performance of a wind turbine or an array of wind turbines. In such modeling applications, it is desirable to have complete data for an annual period. However, equipment failure or extreme weather events can result in incomplete data. For certain models to run properly and achieve the best results, it is necessary to estimate the missing data. The estimated wind-speed values should replicate, as closely as possible, the time-scale properties and statistical characteristics of the missing data.

One complete year of data from three sites in different wind regimes was used to test three different data estimation techniques by creating a sufficient number of gaps (sequences of missing values) of various durations to simulate annual data recovery rates of 90% and 80%. Then three modeling techniques were used to estimate the missing data.

The accuracy of the estimated data was determined by comparing the statistical characteristics (average, standard deviation, and root-mean-square error) of the estimated data to those derived from the corresponding original data values. The estimated data were compared to the original wind-speed data, and also used as input to the Wind Power Simulator (WIPS) model[1]. The model results from the time series with the estimated data were compared to those from the original, complete time series.

The results showed that all three estimation techniques did quite well in replicating the data in the original time series and each worked best at one of the three sites. Errors in the estimated average wind speed were rather small, mostly within ±5%. The errors in theoretical energy from the WIPS model for the entire year of data were mostly on the order of 2% or less. Errors tended to increase with gap length but there was no significant difference in results for the two simulated recovery rates.

INTRODUCTION

In wind energy analysis, time series of hourly average wind speed are often used in computer models to estimate energy output for a single wind turbine or an array of wind turbines. These models are frequently used to help planners, decision-makers, and developers decide whether or not to build wind power plants. The time periods for such modeling are typically on the order of a year or more.

However, for various reasons, the time series of hourly average wind speeds are sometimes incomplete. Anyone using such data is forced to deal with the missing values and has two choices. The first is to ignore the missing data and normalize the results from the computer model by the data recovery rate. This assumes that the wind-speed distribution for the missing hours is accurately represented by the wind-speed distribution of the observed data. A second choice is to estimate the missing hours by some technique that will replicate the missing data accurately.

If data from another site nearby is available, this can be used to estimate the missing data by correlations and linear regression or some other method. Otherwise, the estimates must be made based only on the characteristics of the data collected at the site. We examine three such techniques here and use the results in a wind energy simulation model.

The modeling application that we used is a wind turbine array model called WInd Power Simulator (WIPS), which was developed at the National Renewable Energy Laboratory (NREL) [1]. Previously, Milligan tested some techniques for estimating missing data values for gaps of up to four hours in duration at two different wind sites [2]. However, the testing of the results did not include comparing energy estimates from WIPS or any other similar application. We tested two of the estimation techniques evaluated in that study, as well as a third, for missing data periods of up to 24 hours in three different wind regimes for simulated data recovery rates of 90% and 80%. The resulting hourly time series were then used in the WIPS model to determine which technique might be best for estimating missing values in hourly average wind-speed time series.

THE DATA SETS

We tested the data estimation techniques for one year of data at three sites. The three sites represent different wind regimes that are or could be capable of supporting wind energy development: a typical California site in the Altamont Pass, one from the Great Plains, Finley, North Dakota, and a trade wind-site, Culebra, Puerto Rico. The data set from the Altamont Pass site is a continuous year from 1990, measured at the 40-meter (131 ft) level. The data for the other two are from a U.S. DOE candidate site program and the year of data was constructed from months with complete data at the sites, because no continuous 12 month period with complete data could be found for either. The measurement level for both of the DOE data sets was 45.7 meters (150 ft).

The Altamont Pass site has a mean wind speed of 6.9 m/s, and shows the high amplitude mean diurnal cycle typical of the region. The frequency distribution at this site yields a Weibull shape factor of 1.6, with a high frequency of rather low winds but an extended “tail” out into higher wind speeds. The Great Plains site has a mean speed of 9.3 m/s, with a Weibull shape factor of 2.4. The trade winds site shows a diurnal pattern typical of such locations, with a mild afternoon peak. Its distribution has a rather high Weibull shape factor of 3.3, with a sharp peak near its mean speed of 7.1 m/s and few hours with high wind speeds.

THE MISSING DATA SETS

The complete annual time series were perforated with data gaps of lengths varying from 4 to 24 hours in four-hour increments (4, 8, 12, 16, 20 and 24 hours). This was done to simulate annual data recovery rates of 90% and 80%. Thus, in the 90% recovery case, there would be 876 missing hours in the year and 1752 missing hours in the 80% recovery simulation. The beginning hour of each data gap was chosen by random number such that no two gaps would overlap. The hours that were “missing” for each site, and for each gap length, were all from different sets of hours and not evenly distributed throughout the year. However, subsequent analysis showed that the average wind speed of the hours that were set to “missing” was fairly close to the annual average for the site.

DATA ESTIMATION TECHNIQUES

We used three techniques to estimate the missing hours in the 36 data sets with the missing hours. Two of these were used by Milligan [2] in his previous work and are known as the Markov Transition Matrix and the Trend Method. The third was recommended after a literature search of data estimation techniques for time series data [3] and is called a Lag-1 Autoregressive Markov Chain.

The Markov Transition Matrix is based on the principle that from one hour (or other time step) to the next, the wind will undergo a transition from one speed to another. The technique involved creating a 25x25 probability matrix of wind-speed transitions determined for each month of data. When a data gap is encountered, a random number is generated and used to estimate the first missing wind speed based upon the observed probability matrix of wind-speed transitions during the month. This estimated speed is the base for the next estimation, and so on, until the gap is filled.

The Trend Method is based on the notion that the wind-speed changes from hour to hour can be grouped in trends of various duration, either positive (increasing) or negative (decreasing). This technique required the analysis of the data sets in a four-dimensional probability matrix: 1) the base speed (the speed at which the trend starts); 2) the direction of the trend (positive or negative); 3) the duration of the trend (how long it continues to increase/decrease); and 4) the magnitude of the trend (the absolute difference between the base speed and the speed when the trend direction changed). When a data gap was encountered, the values would be estimated by first completing the current trend, and then finish filling the gap by selecting appropriate trends that would fit the next observed data point at the end of the gap. The final speed of one trend would act as the base speed for the next. Depending upon the length of the data gap, one or more trends would be needed to fill it in. The trend method required analyzing the entire year to develop a suitably-filled probability matrix to complete the various data gaps. Analyzing only one month at a time left too many holes in the matrix to do the job.

The third technique is the Lag-1 Autoregressive Markov chain. This method is described by Equation 1 below:

Equation 1. $$x_t = \hat{f}(x_{t-1} - \bar{x}) + s(1 - \hat{f}^2)^{1/2} A_t + \bar{x} .$$

In this equation, x_t is the missing value being estimated; $\hat{f}$ is the lag-1 autocorrelation coefficient; x_{t-1} is the value preceding the missing value; $\bar{x}$ is the diurnal average for the hour being estimated (from the observed data); s is the diurnal standard deviation for the hour being estimated; and A_t is a pseudo-random number (essentially for noise) generated from a normal distribution, with mean = 0 and variance = 1.

We used the diurnal means and standard deviations instead of monthly, because it was anticipated that this would help preserve the diurnal character of the wind, particularly where there was a pronounced diurnal pattern. In locations where there was little or no discernible diurnal pattern, such as the Great Plains site, using the diurnal means rather than the monthly mean would probably have little effect on the results because the individual means for each hour vary so little from the monthly mean.

In this approach, each month of data was analyzed to calculate the lag-1 autocorrelation and the diurnal means and standard deviations of the hourly wind speeds. The data gaps were filled by solving Equation 1 for each missing value.

One feature of all of the models is a forced convergence to the next good data value in the time series, after a data gap. For each month, the standard deviation of the hour-to-hour wind-speed differences is calculated. This gives a statistical measure of how much the wind speed typically changed from one hour to the next. The convergence was done by looking ahead in the time series to the next good value at the end of the data gap. As the gap was being filled, the estimated values were required to approach the next good value in such a way that the difference between it and the last estimated value was within two standard deviations of the hour-to-hour wind-speed differences. This was done in order to maintain continuity in the modeled data values and not produce large, unreal step functions in the wind-speed time series. Additionally, in the Autoregressive and Markov models this same restriction was put on each estimation of an hourly wind speed. The implications of this restriction are discussed in the Conclusions section of this report.

SCORING CRITERIA

Quantities that describe wind conditions at prospective wind energy sites include the annual average wind speed, the variance of the hourly average wind speeds, the autocorrelation function of the hourly average wind speeds, the mean diurnal wind speeds and the wind-speed frequency distribution. Determining which data estimation technique worked the best in the various permutations of site, data gap length, and simulated data recovery rate was based upon the models' ability to produce wind-speed values that resemble the original data in terms of the characteristics named above.

We compared the estimated wind-speed values and the original values in terms of average wind speed ratios, ratios of the standard deviation of the hourly averages, and root-mean-square (RMS) errors between the estimated and the original speeds. The entire annual time series, containing the estimated wind speeds, were compared to the original, complete time series for the autocorrelation, mean diurnal wind speeds, and energy generation calculations.

RESULTS

We calculated ratios of modeled to observed average speed and standard deviation of the hourly average speeds, as well as RMS errors for each model type and data gap length. Because of space limitations, we cannot show the complete tables and graphs of results. A technical paper, with complete results of this and prior data estimation work, entitled *Estimating Missing Data in Hourly Wind Speed Time Series for Wind Energy Applications*, will be available from NREL in the near future. To determine the best overall performance in each category of evaluation, the we calculated the average and standard deviation of the various ratios (or errors) for each model type and each gap length. The average shows the relative performance between model types or gap lengths and the standard deviation is an indication of the consistency of the modeling.

AVERAGE WIND SPEED

In general, all models did a good job of estimating the missing wind speeds. Many estimated average wind speeds were within 5% of the observed values. This was true for both the 90% and 80% recovery rates. In fact, there was no consistent difference in results between the two recovery rates. The overall accuracy of all models was generally better for shorter gap lengths up to 12 hours and errors tended to increase for longer gap lengths, although the longest gap length did not necessarily have the largest errors. There was also higher variance in the different models' estimates as gap length increased.

The average wind speed for all estimated data were compared, as a ratio, to the average of the original missing data. For the Altamont Pass site, the Markov model (average ratios of 1.020 @ 90% data recovery, 1.009 @ 80% data recovery) was slightly better than the Autoregressive model (average ratios of 1.031 @ 90% data recovery, 1.014 @ 80% data recovery), with the Trend being third by a slight margin (average ratios of 0.971 @ 90% data recovery, 0.984 @ 80% data recovery). However, the Autoregressive result was more consistent (less variance) in its results than the other two. The Autoregressive and Markov models tended to overestimate the average wind speeds, whereas the Trend underestimated them.

At the Great Plains site, the Autoregressive model performed slightly better overall than the others (ratios=0.993 @ 90%, 1.007 @ 80%), but had the highest variance in its estimates of mean speed. The Markov fared the worst (0.968 @ 90%, 1.008 @ 80%).

At the trade winds site, the models had the most difficulty with the moderate data gaps of 12 and 16 hours. All ratios tended to decrease with increased gap length up to 16 hours, then they increased as the gap length continued to increase. While the Trend model showed good overall accuracy in the mean speed estimates, it was less consistent than the other models in making them. The Markov model showed the best performance here, considering the overall averages (0.987 @ 90%, 0.997 @ 80%) and the relatively low variance of the estimates.

STANDARD DEVIATION OF HOURLY AVERAGE WIND SPEEDS

The variance in the modeled hourly average wind speeds is represented by the standard deviation of the modeled hourly average wind speeds as compared to the original data. In general, the models underestimated the variance in the wind speeds. Not that it was lower in all cases, but this was the tendency.

In the Altamont Pass estimates, the Markov model had the variance closest to that in the observed data (avg. ratios=0.976 @ 90%, 0.973 @ 80%). The variance from the Autoregressive model was the lowest in most cases (avg. ratios=0.915 @ 90%, 0.897 @ 80%). There was no clear tendency for the ratios to either increase or decrease as gap length increased.

At the Great Plains site, there was again the tendency to underestimate the variance in the hourly average wind speeds, except for with the Markov and Trend methods at the 80% recovery level. These two had almost identical results on the average (average ratios approximately 1.00), but the Markov results were more consistent. The Autoregressive model had the lowest averages and the greatest range of values in the ratios. There was no clear pattern in the ratios as a function of gap length except that on the average they were all approximately 0.96 for gap lengths less than 24 hours and approximately 1.03 for the 24 hour gap.
For the trade winds site the Autoregressive model produced hourly averages with lower than observed variance (average ratios=0.939 @ 80%, 0.954 @ 80%) and the Trend had a strong tendency to overestimate the variance (average ratios=1.058 @ 90%, 1.056 @ 80%). The Trend also was more erratic, having the highest standard deviation of its ratios for the various data gap lengths. Overall, at this site, the Markov model had the best performance (average ratios=0.978 @ 90%, 0.988 @ 80%) and relatively low standard deviations of these ratios.

RMS ERROR BETWEEN MODELED AND OBSERVED DATA

The RMS error between the modeled hourly averages and the observed was calculated for all estimated hours. In general, the RMS errors increased for all models as data gap length increased. This is not a surprising outcome and does not necessarily mean that the models failed to produce reasonable wind-speed estimates. It is more important that the modeled data be similar to the observed data in a statistical sense, with similar average, variance, autocorrelation, and frequency distributions, rather than being able to match up, hour-to-hour with the original data.

The correlation coefficient between the modeled and observed hours was calculated (although not presented here). Not surprisingly, there was a clear tendency for the correlation to decrease as the data gap length increased. This does not necessarily indicate poor model performance either, but if the RMS errors and correlation coefficients were low and high, respectively, this would lead one to suspect that the model results were good in terms of replicating the observed data.

At the Altamont Pass site, the analysis showed a clear distinction between the model types and their performance. The Autoregressive model had the lowest RMS errors (~2.1 m/s to ~4.0 m/s) and the lowest standard deviation of RMS errors, indicating a higher degree of consistency in the RMS errors for all gap lengths. The Trend method had the highest mean RMS errors (~4.2 m/s) and standard deviation of RMS errors. The tendency to have higher RMS errors as gap length increased also shows up clearly, although it is interesting to note that the RMS errors did not necessarily continue to increase with gap length; they peaked at around 16 to 20 hours for most of the model situations.

The results at the Great Plains site were similar to those at Altamont Pass in that the Autoregressive model had the lowest RMS errors and the Trend method had the highest. In absolute terms the errors from the Autoregressive model were larger than with the Altamont Pass site and the errors with the Trend were a bit lower, although not by a significant margin in either case. Errors from the Markov model were almost the same as at the Altamont. There was also the tendency to have higher errors with increasing gap length with peak errors at a gap length of 16 hours. The errors tended to stabilize or decrease at longer gap lengths. Despite having much higher average wind speeds, the RMS errors at the Great Plains site were very similar in magnitude to those from the Altamont Pass site (~2.3 m/s to ~5.1 m/s).

The trade winds site had the lowest RMS errors of the three sites that were modeled; in many cases they were only half as large (approximately 1.3 m/s to approximately 3.0 m/s) as at the other sites. This could be because this site had the fewest high wind speeds and had the lowest variance in hourly wind speeds. It appears that the models did not replicate the high wind speeds well and since the trade winds site had fewest of these, there were lower resultant RMS errors. There was again the same pattern of increasing RMS errors with data gap length. For the 90% simulated recovery and all model types, the errors peaked at 12 to 20 hours and then dropped. But at 80% simulated recovery, the RMS errors increased steadily with gap length for all three model types. The Autoregressive and Markov models had nearly identical RMS errors. The Trend produced the highest RMS errors for the trade winds site.

It is worth noting that, at all three sites, the RMS errors at 90% recovery and those at 80% recovery were very close. The most significant change in RMS errors was associated with increases in gap length and those seemed to peak more often at 16 to 20 hours and were a bit lower at 24 hours.

MEAN DIURNAL WIND SPEEDS

We compared the mean diurnal wind speeds for the data sets with estimated values to the mean diurnal wind speeds calculated from the observed data and an error calculated for each of the 24 averages. As a way of grading the accuracy of the data sets with estimated wind speeds, we calculated the RMS error of the 24 errors at each site and for each data estimation technique. In general, the RMS errors in the diurnal means were small.

For the Altamont Pass site, which had the strongest diurnal pattern, the largest error for any one hour during the day was 0.2 m/s. Most errors were either 0.0 m/s or 0.1 m/s. The errors were a bit larger in the 80% recovery simulation than in the 90% case. The Autoregressive model had the lowest average and standard deviation of RMS errors. The Trend method did a bit better than the Markov model in this respect, although the Trend model had slightly larger standard deviation of the RMS errors. The average RMS errors showed a gradual increase as the gap length increased, at least up to the 20 hour gap. The mean RMS errors by hour of day reveal that the Markov and Trend models had peak errors during the times of the diurnal maximum and minimum wind speeds. This effect was accentuated in the 80% recovery case. The Autoregressive model probably performed better in this respect because it used the observed diurnal mean wind speeds as part of Equation 1 to calculate the wind speed at any given time.

At the Great Plains site, the RMS errors in mean diurnal wind speed were quite similar for all three models and for the two simulated recovery rates. The errors were a bit larger in the 80% case than in the 90% case. Again, the errors tended to increase with data gap length up to 20 hours and then decreased. The lowest errors overall were obtained with the Trend model. Accuracy in the mean diurnal wind speeds at this site is not of particular importance since the diurnal pattern at the Great Plains site was not distinct to begin with.

The RMS errors in the mean diurnal wind speeds were lower at the trade winds site than at both the Altamont and Great Plains sites (average RMSE < 0.1 m/s). There was a slight tendency for the mean RMS errors to increase with increasing gap length. At the trade winds site there was more of a diurnal pattern than at the Great Plains site so the models' ability to maintain the diurnal characteristics of the winds at this site would be more of a significant factor. The Markov and Trend models had their greatest errors, on the average, during the midday peak in wind speeds at the trade winds site. During these times the Autoregressive model had errors no larger than at other times of the day. This is probably due to the same reasons that the Autoregressive model performed better in this regard at the Altamont Pass site, i.e., it uses the observed mean diurnal wind speeds in its estimation equation.

WIPS ENERGY CALCULATIONS

The previous statistical analyses point out how well the modeled wind-speed values replicate the observed data that they are trying to emulate. The real proof, in the application of these data, is in how accurately they replicate the results of a theoretical energy calculation. The WIPS model was used to calculate annual theoretical energy from a 110 MW array of 300-kW, stall-regulated wind turbines. We ran the model for all cases of estimated wind data and compared each energy calculation to the energy calculation from the observed data. In all, there were 108 cases examined. The analysis of results was made simple. Only the ratio of annual energy (including estimated data/observed data only) was calculated. In most cases the errors in theoretical energy were within ±2%. As expected, the errors in energy followed the errors in average wind speed.

At the Altamont site, the differences in model performance were very small. The Autoregressive model had the best overall accuracy and the lowest variance in the energy calculations, but only very slightly so. The largest errors were from the Trend model in the 80% recovery simulation. The 80% case proved to have the highest errors and the greatest variance in the individual energy ratios. There was no clear pattern in the average ratios as a function of data gap length, however the variance in the ratios did increase up to a peak at the 20 hour gap length and then drop at the 24 hour gap length.

With the Great Plains site, there was a high degree of accuracy, overall, in the energy estimates using the modeled data. A majority of the energy calculations were within 1% of the value produced from the observed data. In fact, the errors in the average ratios for all model types and both recovery rates were all less than ±1%. The variance in energy ratios in the 90% case was lower than in the 80% case.

At the trade winds site the energy estimates using the estimated data agreed very well with the observed data as indicated by the average ratios. As with the Great Plains and Altamont Pass sites, many of the individual energy estimates were within 1% of the one made using the observed data. The largest errors were just over 2%. At this site, the projections made with the Markov model were the most accurate. The ones made with the Autoregressive model were the most consistent; i.e., the standard deviations of the ratios were the lowest overall, but only slightly so. In general, the models underestimated the energy consistently for gap lengths of 12 and 16 hours, following the average wind speed estimates.

A separate calculation of theoretical energy from a single turbine was done by the method of bins using the power curve for a 600 kW wind turbine. Calculations were done for all estimated data sets at the three sites and for the data sets with the missing values. The energy estimates from the data sets with missing values were normalized by their data recovery rate (0.90 or 0.80) to scale them for the entire year of data. It turns out that the normalized energy values were generally as accurate as the energy values obtained by using the estimated data, often within 1% of the value from using the complete, original data set. In a number of cases, the calculations with the estimated data were less accurate than when the data sets with missing data were used and the result normalized by the recovery rate.

This would seem to make the job of estimating missing data an unnecessary exercise. However, one must consider that the missing data blocks were randomly selected throughout the year and in the real world this would not necessarily be the case. Also, in this controlled test, we know what the missing data are. In the real world, there would still be the uncertainty of not knowing and the desire to have the best available estimate of what the data *would have been*.

CONCLUSIONS

It must be stated that the results presented in this report came from one run of each gap-filling model. Subsequent runs would produce results which may vary from those presented here. Without doing this there is no way of knowing whether the results of this work represent a true indication of the models' ability to replicate winds from the various sites. That is, the stability of the different models' results cannot be guaranteed or even estimated at this time. However, extreme differences would not be expected.

Modification of model parameters could produce improvements in some aspects of the model performance. One possible adjustment would be the allowable difference between consecutive wind-speed estimates in the case of the Autoregressive and Markov models. Increasing this value would probably increase the variance and perhaps the accuracy in the modeled wind-speed values.

There are many different ways of reviewing the results in order to determine which model is superior for making wind-speed estimations. Three very different wind regimes were used in the testing. So it would be useful to determine which model type worked best in each of these. A set of objective criteria was used to score the results, using a system of points added or deducted for good or poor performance, respectively.

The scoring was done twice. The first time scoring criteria were applied to five categories of performance: average wind-speed ratio, ratio of standard deviation of the hourly average wind speeds, RMS errors of the hourly estimates, RMS error of the diurnal mean speeds, and energy output from WIPS. The second time scoring was based on only what was deemed to be the two most important categories, average wind speed and WIPS energy estimates. However, since the two are inextricably linked, using them may effectively result in one criterion determining the winner. The autocorrelations were not used in either scoring scenario because the results were so consistent (and close to those from the original data) that there was not enough difference to warrant inclusion in the scoring.

For the first case, with five categories, two positive points were awarded to a model for being the most accurate in a category and one for being the most consistent (lowest standard deviation of the results). Two negative points were awarded for being the worst in a category and one for being the least consistent (highest standard deviation of the results). If there was a tie for any division in any category, the appropriate score would be awarded to the models that tied. For the second case (only two categories) the points awarded for average wind speed were the same as for the first scoring case but for the WIPS performance the point magnitudes were increased by one, since having good energy estimates is more important than average wind speeds. Net totals were made for the 90% and 80% cases and then for both simulated recovery rates combined.

The scoring shows that for the Altamont Pass site, the Autoregressive model had the best performance. The Trend Method had the worst scores. At the Great Plains site, the Trend wound up with the best combined score. The Markov was just mediocre and ended up the worst overall at this site. In the trade wind regime, the Markov model was the best overall. The Trend model had the worst combined score at this site.

So using all five of the performance categories, each model type was best at one site, the Autoregressive model in the Altamont regime, the Trend at the Great Plains and the Markov model in the trade wind regime. The worst performer in the Altamont Pass and trade wind regimes was the Trend Method. The Markov model had the worst score at the Great Plains site.

Now considering the scoring of the analysis results using the more limited performance categories, average wind speed and WIPS energy output ratios, the models were rated again. The results were very similar to the scoring for all five categories. The same models did the best at the same sites, although the margins were not the same. It is arguable that the scoring method was weighted too heavily on the wind speed since WIPS performance depends upon it completely.

In terms of data gap length, best and most consistent results were obtained, not surprisingly, with the shortest gap lengths. The largest errors in most cases occurred with gap lengths in the range of 16 to 20 hours. It is not clear why this would be so rather than for the longest gap length, 24 hours.

RECOMMENDATIONS

All three models produced reasonable estimations of the missing data. The Autoregressive and Markov models were generally more accurate and tended to be more consistent. They were the easiest to program, too.

At sites with large diurnal amplitudes, the Autoregressive model using the diurnal averages and standard deviations in the estimation equation would seem to be the best choice. The Markov model might perform better at sites with a strong diurnal component (like the Altamont) if a third dimension (time of day) were added to the matrix analysis. However, depending on how this were done, it could make it difficult to fill in enough cells in this new matrix to ensure a successful run of the model. This could be remedied by reducing the size of the matrix and increasing the bin width. The Markov model tended to be less likely to do the best or the worst and might be a good compromise for any type of wind regime. The Trend model had a greater tendency to do the worst, although it was the best for the Great Plains site and might be the best choice for sites without a distinct diurnal pattern.

The programming of the Trend model was most difficult and anyone who uses this method would be advised to reduce the number of bins in the "base wind speed," "duration" and "magnitude" categories, giving each of them a wider bin width. This would make it easier to fill in the possible combinations of all the various dimensions and simplify the process of finding a suitable trend to fill a gap. The Trend model would probably work better at a site with a strong diurnal pattern if there were an additional dimension of "hour-of-day when a trend started," but not necessarily 24 of these bins.

It would be interesting to test these and possibly other estimation techniques for situations in which data were missing for extended periods of time, for example, up to a month. This situation is, sadly, not uncommon in real world wind monitoring.

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